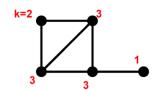
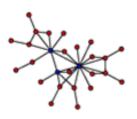


# Data Analysis I

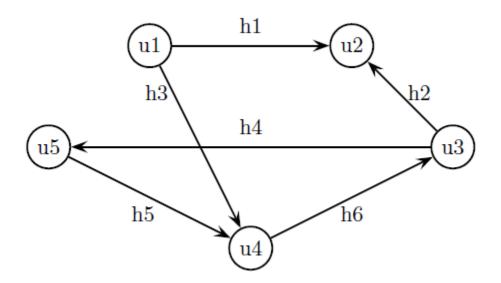
**Graph Representation** 

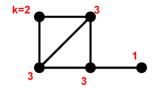


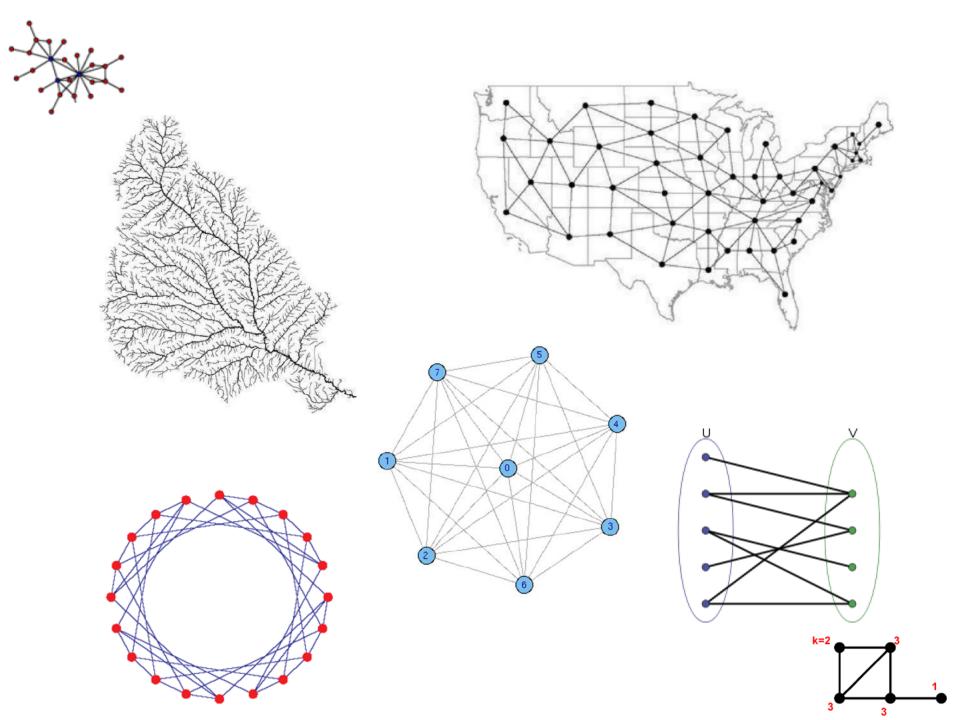


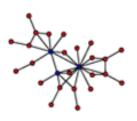
# Graph representation

• By image (drawing) ☺



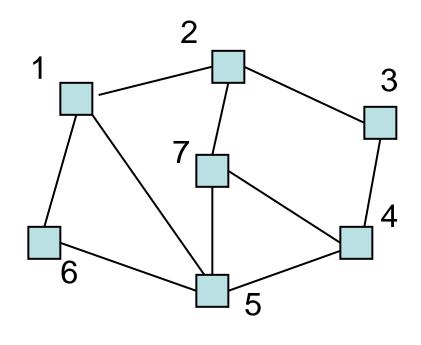


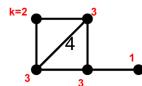


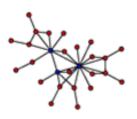


# Implementing a Graph

- To program a graph data structure, what information would we need to store?
  - For each vertex?
  - For each edge?

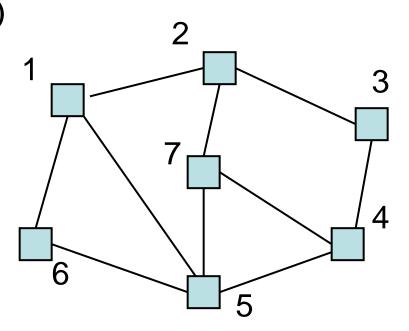


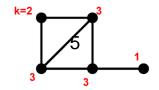


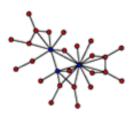


# Implementing a Graph

- What kinds of questions would we want to be able to answer (quickly?) about a graph G?
  - Where is vertex v?
  - Which vertices are adjacent to vertex v?
  - What edges touch vertex v?
  - What are the edges of G?
  - What are the vertices of G?
  - What is the degree of vertex v?

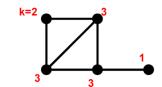


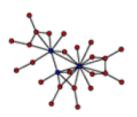




## Representation

- There are different ways to represent a graph
  - List of edges
  - List of lists: Node list and list of neighbors
  - Adjacency matrix

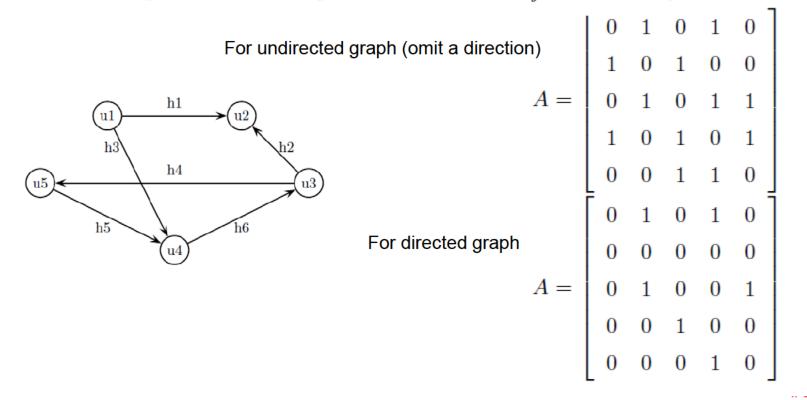




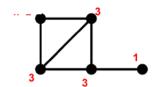
## Adjacency matrix

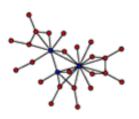
$$A_{ij} = \begin{cases} w_{ij} & \text{if } i \text{ and } j \text{ are connected} \\ 0 & \text{otherwise} \end{cases}$$

If A represents an unweighted network, then  $w_{ij} = 1$  for all i, j.



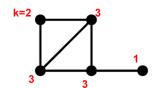
$$A =$$

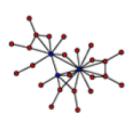




# Adjacency matrix

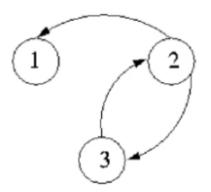
- Adjacency is chosen on the ordering of vertices.
   Hence, there as are as many as n! such matrices.
- The adjacency matrix of undirected graphs are symmetric (a<sub>ij</sub> = a<sub>ji</sub>) (why?) → redundant information for undirected graphs
- When there are relatively few edges in the graph the adjacency matrix is a sparse matrix
- Directed multigraphs can be represented by using  $a_{ij}$  = number of edges from  $v_i$  to  $v_j$ , undirected similarly





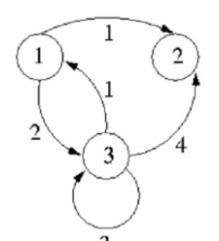
# Modifications of adjacency matrix

- Weighted adjacency matrix
- Distance matrix (e.g. result of Floyd's algorithm (later))
- Similarity matrix (later)



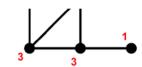
Directed

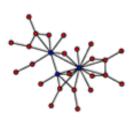
$$A = \left(\begin{array}{ccc} 0 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{array}\right)$$



Directed Weighted

$$A = \left(\begin{array}{ccc} 0 & 1 & 2 \\ 0 & 0 & 0 \\ 1 & 4 & 3 \end{array}\right)$$

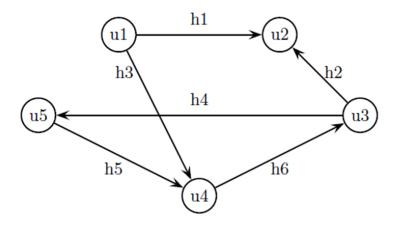




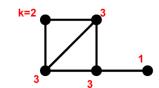
### Incidence matrix

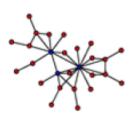
• Let G = (V, E) be an unditected graph. Then the incidence matrix with respect to this ordering of V and E is the n x m matrix  $B = [b_{ij}]$ , where

$$b_{ij} = \begin{cases} 1 \text{ when edge } e_j \text{ is incident with } v_i \\ 0 \text{ otherwise} \end{cases} \quad B = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$



$$B = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 \\ -1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & -1 \\ 0 & 0 & -1 & 0 & -1 & 1 \\ 0 & 0 & 0 & -1 & 1 & 0 \end{bmatrix}$$





# List of lists: Node list and list of neighbors (Adjacency list)

#### https://en.wikipedia.org/wiki/Adjacency\_list

#### Undirected graph

$v_1$	$\rightarrow$	$v_2$ .	$v_4$
_			

#### $v_2 \rightarrow v_1, v_3$

$$v_3 \rightarrow v_2, v_4, v_5$$

$$v_4 \rightarrow v_1, v_3, v_5$$

$$v_5 \rightarrow v_3, v_4$$

#### Directed graph

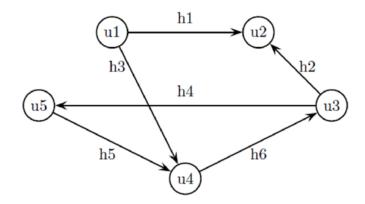
$$v_1 \rightarrow v_2, v_4$$

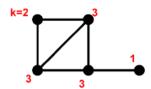
$$v_2 
ightarrow$$

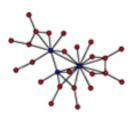
$$v_3 
ightarrow v_2, v_5$$

$$v_4 
ightarrow v_3$$

$$v_5 
ightarrow v_4$$

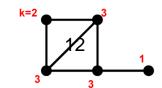


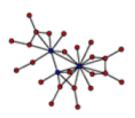




# Node list and list of neighbors: Pros and Cons

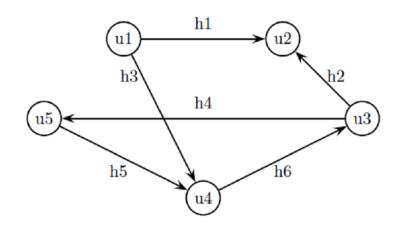
- Adjacency list stores edges as individual linked lists of references to each vertex's neighbors
- advantages:
  - new nodes can be added easily
  - new nodes can be connected with existing nodes easily
  - "who are my neighbors" easily answered
- disadvantages:
  - determining whether an edge exists between two nodes: O(average degree)

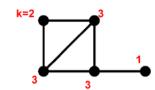


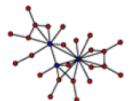


# List of edges

Undirected graph	Directed graph
$(v_1,v_2)$	$(v_1,v_2)$
$(v_1,v_4)$	$(v_1,v_4)$
$(v_2, v_3)$	$(v_3, v_2)$
$(v_3,v_4)$	$(v_3, v_5)$
$(v_3, v_5)$	$(v_4,v_3)$
$(v_4, v_5)$	(v5, v4)







### Runtime table

2 L	<del>(G)</del>	C CGDIC			
<ul> <li>n vertices, m edges</li> <li>no parallel edges</li> <li>no self-loops</li> </ul>	Edge List	Adjacency List	Adjacency Matrix		
Space	n + m	n + m	<b>n</b> <sup>2</sup>		

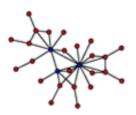
•			
Space	n + m	n + m	<b>n</b> <sup>2</sup>
Finding all adjacent	m	deg( <b>v</b> )	n

vertices to **v** Determining if **v** is  $deg(\mathbf{v})$ m adjacent to w

 $n^2$ adding a vertex

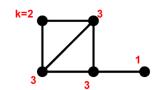
adding an edge to  ${m v}$  $deg(\mathbf{v})$  $n^2$ removing vertex v m removing an edge from **v** 

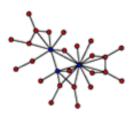
 $deg(\mathbf{v})$ m



# Data Analysis I

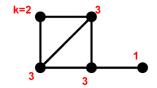
Measures and Metrics

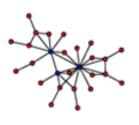




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   Cambridge University Press. [97-102]
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- Albert-László Barabási. Network Science <u>http://barabasi.com/networksciencebook/</u>
   Chapter 2

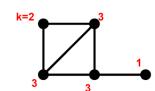


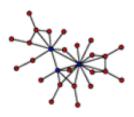


# Structural (topological) properties

- Degree
- Local degree d of a node  $v_i$  (as the number of its neighbors)  $d_i = \sum_i A(i,j)$
- Global mean (average) degree  $\mu_d = \frac{\sum_i d_i}{n}$
- indegree / outdegree (by taking the summation over the incoming / outgoing edges) as follows:

$$id(v_i) = \sum_{j} A(j, i)$$
$$od(v_i) = \sum_{i} A(i, j)$$



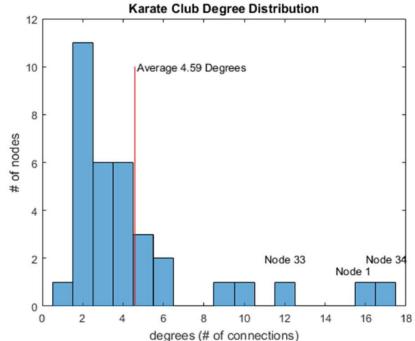


## Degree centrality

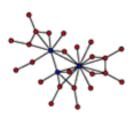
- Degree centrality
- Social network the higher the degree, e.g., a more influential person

 The citation network - the higher the degree (more references), the "greater the impact of the publication on scientific research,"

Zachary's carate club

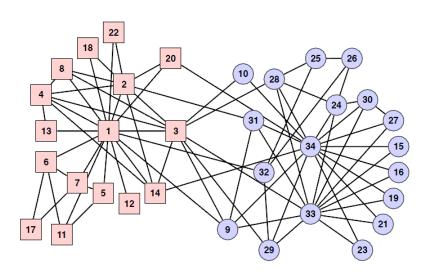


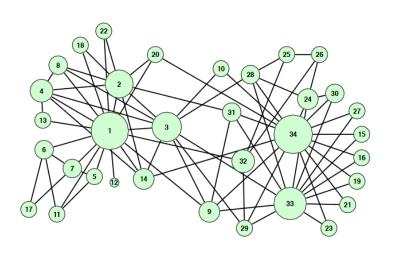




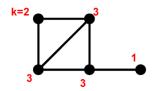
# Degree centrality

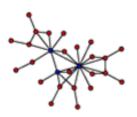
Zachary's carate club





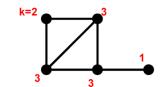
group 1	1	2	3	4	5	6	7	8	11	12	13	14	17	18	20	22		
k	16	9	10	6	3	4	4	4	3	1	2	5	2	2	3	2		
k/m	0.10	0.06	0.06	0.04	0.02	0.03	0.03	0.03	0.02	0.01	0.01	0.03	0.01	0.01	0.02	0.01		
group 2	9	10	15	16	19	21	23	24	25	26	27	28	29	30	31	32	33	34
$\overline{k}$	5	2	2	2	2	2	2	5	3	3	2	4	3	4	4	6	12	17
k/m	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.03	0.02	0.02	0.01	0.03	0.02	0.03	0.03	0.04	0.08	0.11

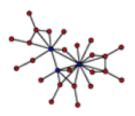




#### Path

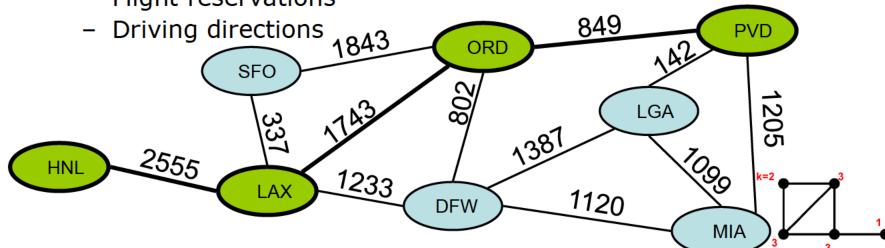
- A path in a graph is a finite or infinite sequence of edges which joins a sequence of vertices which, by most definitions, are all distinct (and since the vertices are distinct, so are the edges).
- The shortest path problem is the problem of finding a path between two vertices (or nodes) in a graph such that the sum of the weights of its constituent edges is minimized.
- The distance between two vertices in a graph is the number of edges in a shortest path (also called a graph geodesic) connecting them. This is also known as the geodesic distance.

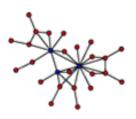




### Shortest Path Problem

- Given a weighted graph and two vertices u and v, we want to find a path of minimum total weight between u and v.
  - Length of a path is the sum of the weights of its edges.
  - In unweighted graph the weights od edges are = 1.
- Example:
  - Shortest path between Providence and Honolulu
- Applications
  - Internet packet routing
  - Flight reservations



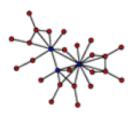


### Structural properties

- Path
- Local
  - The eccentricity  $e(v_i)$  of a node  $v_i$  is the maximum distance from  $v_i$  to any other node in the graph  $e(v_i) = \max_i \{d(v_i, v_j)\}$
- Global
  - The diameter d(G), is the maximum eccentricity of any vertex in the graph  $d(G) = \max_{i} \{e(v_i)\} = \max_{i} \{d(v_i, v_j)\}$
  - Mean distance (Average Path Length) of a connected graph is given as  $\sum_{i} \sum_{i=j} d(v_i, v_i) = 2$

$$\mu_{L} = \frac{\sum_{i} \sum_{j>i} d(v_{i}, v_{j})}{\binom{n}{2}} = \frac{2}{n(n-1)} \sum_{i} \sum_{j>i} d(v_{i}, v_{j})$$

- where n is the number of nodes in the graph, and  $d(v_i, v_j)$  is the distance between  $v_i$  and  $v_j$ .



### All-Pairs Shortest Paths

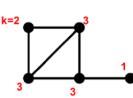
- Find the distance between every pair of vertices in a weighted directed graph G.
- Floyd-Warshall algorithm
- https://en.wikipedia.o rg/wiki/Floyd%E2%80 %93Warshall algorith m
- https://www.youtube. com/watch?v=40QeC uLYj-4

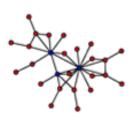
```
Algorithm AllPair(G) {assumes vertices 1,...,n}
for all vertex pairs (i,j)
   if i = j
      C_0[i,i] \leftarrow 0
   else if (i,j) is an edge in G
      C_0[i,j] \leftarrow weight of edge(i,j)
   else
      C_0[i,j] \leftarrow + \infty
for k \leftarrow 1 to n do
   for i \leftarrow 1 to n do
     for j \leftarrow 1 to n do
        C_k[i,j] \leftarrow \min\{C_{k-1}[i,j], C_{k-1}[i,k] + C_{k-1}[k,j]\}
return C_n
```

Uses only vertices numbered 1,...,k-1 (compute weight of this edge)

Uses only vertices k=2 numbered 1,...,k-1

Uses only vertices numbered 1,...,k





# Example: Floyd-Warshall

$$C^{0} = \begin{bmatrix} 0 & 3 & 5 & x & x \\ x & 0 & 1 & 2 & x \\ x & x & 0 & x & x \\ x & x & 9 & 0 & 1 \\ 2 & x & 8 & x & 0 \end{bmatrix} C^{1} = \begin{bmatrix} 0 & 3 & 5 & x & x \\ x & 0 & 1 & 2 & x \\ x & x & 0 & x & x \\ x & x & 9 & 0 & 1 \\ 2 & 5 & 7 & x & 0 \end{bmatrix}$$

$$C^{1} = \begin{vmatrix} 0 & 3 & 3 & x & x \\ \hline x & 0 & 1 & 2 & x \\ \hline x & x & 0 & x & x \\ \hline x & x & 9 & 0 & 1 \\ 2 & 5 & 7 & x & 0 \end{vmatrix}$$

$$v_1 \longrightarrow (v_2, 3), (v_3, 5)$$

$$v_2 \longrightarrow (v_3, 1), (v_4, 2), (v_5, 4)$$

$$v_3 \longrightarrow$$

$$v_4 \longrightarrow (v_3, 9), (v_5, 1)$$

$$v_5 \longrightarrow (v_1, 2), (v_3, 8)$$

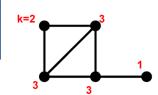
$$C^2$$

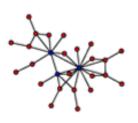
$$C^{2} = \begin{bmatrix} 0 & 3 & 4 & 5 & x \\ x & 0 & 1 & 2 & x \\ \hline x & x & 0 & x & x \\ \hline x & x & 9 & 0 & 1 \\ 2 & 5 & 6 & 7 & 0 \end{bmatrix}$$

$$C^{2} = \begin{bmatrix} 0 & 3 & 4 & 5 & x \\ x & 0 & 1 & 2 & x \\ \hline x & x & 0 & x & x \\ \hline x & x & 9 & 0 & 1 \\ 2 & 5 & 6 & 7 & 0 \end{bmatrix} \quad C^{3} = \begin{bmatrix} 0 & 3 & 4 & 5 & x \\ x & 0 & 1 & 2 & x \\ \hline x & x & 0 & x & x \\ \hline x & x & 9 & 0 & 1 \\ \hline 2 & 5 & 6 & 7 & 0 \end{bmatrix}$$

$$C^{4} = \begin{bmatrix} 0 & 3 & 4 & 5 & 6 \\ x & 0 & 1 & 2 & 3 \\ x & x & 0 & x & x \\ x & x & 9 & 0 & 1 \\ \hline 2 & 5 & 6 & 7 & 0 \end{bmatrix} \qquad C^{5} = \begin{bmatrix} 0 & 3 & 4 & 5 & 6 \\ 5 & 0 & 1 & 2 & 3 \\ x & x & 0 & x & x \\ 3 & 6 & 7 & 0 & 1 \\ 2 & 5 & 6 & 7 & 0 \end{bmatrix}$$

$$C^{5} = \begin{bmatrix} 5 & 5 & 4 & 5 & 5 \\ 5 & 0 & 1 & 2 & 3 \\ x & x & 0 & x & x \\ 3 & 6 & 7 & 0 & 1 \\ 2 & 5 & 6 & 7 & 0 \end{bmatrix}$$

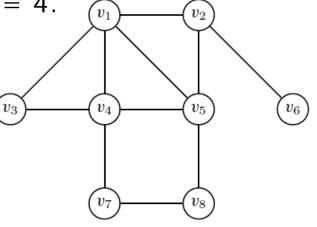


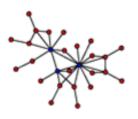


# Structural properties

- Degree sequence of the graph on the figure is (4,4,4,3,2,2,1) and therefore its degree frequency distribution is given as  $(N_0,N_1,N_2,N_3,N_4) = (0,1,3,1,3)$
- Mean degree is 2.75
- The degree distribution is given as  $f(k) = P(X = k) = N_k/n$ (f(0), f(1), f(2), f(3), f(4))=(0,0.125,0.375,0.125,0.375)
- The eccentricity of node  $v_4$  is 3, because the node farthest from it is  $v_6$  and  $d(v_4,v_6)=3$ .

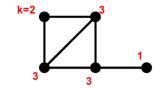
• The diameter of the graph is d(G) = 4, as the largest distance over all the pairs is  $d(v_6, v_7) = 4$ .

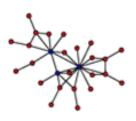




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   Chapter 2





# Structural properties (global)

- Network dimension networks are usually large, i.e. the number of vertices is large
- Network density Networks are usually sparse
  - Sparse vs. dense graph (net)
  - The resolution is often vague, depending on the context
  - Most often
    - Sparse graph  $n \approx km$ , m = O(n)
    - Dense graph  $m = \Theta(n^2)$
  - Density H:
    - mean degree <d> = 2m/n → after the of division by highest degree (n-1) →
    - 2m/n\*(n-1) →
    - $H = m / 0.5*n*(n-1), H \in <0,1>$

